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Socio-economic and demographic predictors of accidental dwelling fire rates

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Abstract

Despite the considerable reduction in rates of fire that have been seen in the UK in recent years analysis of three years of service data from a large UK fire service reveals that there continue to be striking inequalities in the way in which fire is distributed through society. The use of principal component analysis (PCA) and ordinary least squares regression enabled the development of a model that explains around one third of the variance in rates of fire at small neighbourhood level using just three predictor variables: the proportion of residents identifying as Black, the proportion of residents who have not worked for more than five years or have never worked, and the proportion of single person households where the resident is aged under 65. The value of PCA in addressing problems of collinearity between potential predictor variables is particularly highlighted. The findings serve to update understanding of the distribution of fire in the light of the ongoing reduction in fire rates of recent years. They will help fire services to target fire safety interventions to those neighbourhoods and communities where they are most needed and have the greatest potential to bring about reductions in the rate of fire.

Keywords

inequality, principal component analysis, linear regression, race, living alone, unemployment, fire, prevention

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1 Introduction

Dwelling fires are a major cause of injury and economic loss. The UK government estimated the total cost of fire in England in 2008 to be £8.3bn ($12.7bn) [1]. Some two thirds of building fires in Britain in 2011-12 were dwelling fires, and these accounted for 76% of the 380 fire related deaths [2]. Over the same period, dwelling fires further accounted for 79% (8,900) of all non-fatal fire casualties, with the vast majority of such fires (85%) attributed to accidental causes.

This paper details an analysis of fire service data which sought to establish how accidental dwelling fires are distributed through different sectors of society and to identify socio-economic and demographic factors which are associated with higher rates of dwelling fire. Drawing on existing literature, potential predictor variables are reviewed and issues involved in their operationalisation are discussed. A major problem facing those analysing the distribution of fire is the potential for collinearity between some of these predictor variables. The paper provides a useful example of the value of principal component analysis in addressing such collinearity. It further helps to update understanding of the unequal distribution of fire in the light of the ongoing reduction in fire rates, as well as identifying an important variable that has received little attention in the past, the number of single person households aged under 65.

1.1 The unequal distribution of dwelling fires

It is well established that dwelling fires are not distributed evenly through society, but that certain sectors experience disproportionate numbers of incidents. An earlier review of much of literature related to this topic found considerable evidence of a social gradient in the distribution of fire, with poverty and deprivation clearly linked to increased numbers of incidents [3]. However, many of the existing studies are now relatively old, and even some recent studies rely on data that dates from over a decade ago [e.g. ,4]. At the same time, the incidence of fire is changing rapidly, with the number of building fires in the UK falling by 39% in the decade to 2012 [5]. Against this changing landscape, if fire services are to target fire safety interventions effectively it is important to establish whether or not the social gradient in exposure to dwelling fires continues to exist. This paper addresses that need by investigating the distribution of accidental dwelling fires resulting in the attendance of fire fighters, using service data from one English fire service, the West Midlands Fire Service (WMFS). As well as describing a method that can be used for analysis of fire incident data in other areas, the paper provides a valuable and up to date insight into the distribution of fire in one major urban area. The findings can reasonably be transferred to areas with a similar character, and with that in mind it is useful to commence by briefly describing the character of the West Midlands.

1.2 The West Midlands county

The WMFS serves the area of the former West Midlands Metropolitan County in England and although that county no longer exists it is useful in the context of discussing the WMFS to refer to the West Midlands county, an area which should not be confused with the geographically larger West Midlands region.

The county covers an almost entirely urban area of 902km^2 (348miles^2) in central England and in 2011 was home to 2.74 million people [6]. It takes in the cities of Birmingham, Coventry and Wolverhampton, along with the metropolitan boroughs of Dudley, Sandwell, Solihull and Walsall, and consists of two conurbations, the larger of which is the second largest urban area in England [7]. The county demonstrates considerable diversity in both economic and demographic terms. Three of its seven local authorities have more than half their population living in the most deprived neighbourhoods in England, whilst Solihull (the only local authority in the county with substantial rural areas) is amongst the least deprived areas in England [8].

Overall, 66% of the county's population considered themselves White British at the 2011 census, with 6.7% Indian, 7.3% Pakistani, 1.8% Bangladeshi, and 6% Black African or Caribbean [6]. A more recent development, following the enlargement of the EU, is the growing number of migrant workers from eastern Europe [9]. As of 2011 the greatest number of these people were from Poland [10].

2 Methods

2.1 Overview

The study was an area based, or ecological, examination of rates of accidental dwelling fire (ADF) across the area served by the West Midlands Fire Service (WMFS). WMFS provided anonymised data on incidents of ADF attended by them between September 2010 and August 2013. These data were analysed with reference to a range of socio-economic and demographic data available from other sources, principally from the UK census of 2011 [6] and the Department of Communities and Local Government's indices of deprivation for 2010 [11].

Analysis was undertaken using SPSS 22 [12] and began with an exploration of correlation between rates of accidental dwelling fire and each of the potential predictor variables. As high levels of collinearity were found between many of the predictor variables used, principal component analysis was then undertaken to identify the main components explaining the difference between areas. Suitable variables were selected that loaded heavily on the identified components and these were used in ordinary least squares regression analysis.

2.2 Choice of geography

When undertaking an area based study such as this the size of the unit of analysis is of some importance. Larger areas are likely to be more heterogeneous and their use will mask the considerable internal variation. On the other hand, small areas, whilst exhibiting less heterogeneity, may encounter too few fire incidents to permit useful analysis, or a single incident may represent a very large proportion, giving rise to extreme outliers in the data. This may result in associations appearing stronger at larger area levels as the impact of outliers is reduced. For this study the Lower Layer Super Output Area (LSOA) was chosen as the unit of analysis as it is the smallest unit at which meaningful numbers of ADF incidents occur. The LSOA is a census unit used in England and Wales and defined by the Office for National Statistics. The boundaries of LSOAs are drawn up after the census is completed in order to allow census data to be used to define areas that were relatively homogeneous at the time of the census, with a population of between 1 000 and 3 000 people [13]. The mean LSOA population in this study was 1628 (n=1680, s=298), with a mean of 3.17 ADF incidents per LSOA (n=1680, s=2.68) across the three year period (September 2010 to August 2013) from which incident data were drawn.

2.3 Representing rates of fire

The WMFS incident data were first aggregated to provide counts of ADF incidents for each LSOA for the period September 2010 to August 2013, using the open source QGIS 2.0 geographical information system [14]. An index of ADF was then calculated for each LSOA using an approach adapted from Corcoran et al. [4]. This index represents the rate of accidental dwelling fire per household expressed as a percentage of the rate that would be expected were incidents evenly distributed.

The use of the number of households merits some further comment as it differs from Corcoran et al's [4] approach, which employed household population (i.e. total population living in households). In considering the rate of incidents an appropriate choice of denominator is the population at risk. In the case of accidental dwelling fire this is, strictly speaking, the number of dwellings in an area rather than the number of people. There is a very close relationship between dwellings and households in the UK census data, with the former derived from the latter. The main difference in figures comes from unoccupied dwellings, which count as a dwelling but not as a household. As numbers of households were already included within the dataset as the denominator for several other statistics (see section 2.4) it was decided to use this figure as the basis for calculating rates of fire. Given the close relationship between the two figures the choice is unlikely to make a material difference to the study. On average the figures differ from each other by 3.1% and Pearson's correlation coefficient between them is 0.991.

A further point of note is that ideally the nominator and denominator should match, so the number of dwellings affected by fire should be used to calculate a rate, rather than the number of fire incidents affecting dwellings. Data relating to the number of dwellings affected were, however, not available. Most recorded incidents affect only a single dwelling and whilst it is possible that some affected more than one dwelling these are likely to be relatively few and to have little impact on results.

2.4 Choice of predictor variables

In surveying the existing literature to inform the choice of potential predictor variables, Jennings' [3] recent review was supplemented by additional studies drawn from the public health literature (which was out of the scope of Jennings' review), together with a number of reports from the UK government and grey literature[1]. As there is some evidence that factors associated with fire are context sensitive (e.g. Corcoran et al report differences between Wales and Australia [15], and some marked differences have been found even between regions of the UK [16]) the focus was on UK based studies as they more closely reflect the context of this study.

The influence of poverty and social deprivation was a consistent finding [3,4], with poor housing quality [3,17], unemployment and lack of economic activity [16,18], and lower educational attainment [19] being aspects particularly noted. Household structure was identified in a number of studies, with lone parents [16] and adults living alone [16,20] both emerging as predictors. Age, though not necessarily associated with rates of fire incidents, has been reported as strongly linked to numbers of fire casualties, particularly in the public health literature [20–23]. Ethnicity has also been found to be associated with rates of fire [4,19], although it has been argued that this is the result of collinearity with poverty and deprivation [16].

Variables related to each of these factors were identified in data from the 2011 UK census. Census data were obtained showing counts of either people or households in each LSOA and for analysis purpose these were all converted to proportions. A summary of census variables used is shown in Table 1, which also indicates which denominator was used in converting counts to proportions.

[1] Literature such as reports and working papers produced and distributed outside of the traditional academic channels of peer-reviewed journal and books

Variable	Denominator
Population	
Number of households	
Population density	
Lone parents households	Households
Households with social landlords	Households
People with poor or no English	Population aged 3 years or over
People for whom English is not their first language	Population aged 3 years or over
Ethnic groups	Population
People who have never worked	Population aged 16-74
People who have not worked for over 10 years	Population aged 16-74
People who have not worked for over 5 years	Population aged 16-74
People with no qualification	Population aged 16 years or over
People without at least a level 2 qualification	Population aged 16 years or over
Households experiencing 0, 1, 2, 3 or 4 domains of deprivation	Households
One person households	Households
One person households, aged 65 or over	Households
One person households, aged under 65	Households
One person households, various age groups	Households
Overcrowded households (households with fewer bedrooms than needed)	Households
Households without central heating	Households
People who are limited a little or a lot by disability	Population
People whose health is bad or very bad	Population
People who were unemployed and seeking work in the week prior to the census	Population aged 16-74
People who were long term sick or disabled-economically inactive	Population aged 16-74

Table 1: Summary of census variables used

2.4.1 Operationalising deprivation

Deprivation can be conceived of as a multi-dimensional concept which includes a range of different factors affecting an individual’s opportunities and access to resources [24]. However, using multi-dimensional variables is potentially problematic when carrying out many statistical analyses, including principal component analysis and regression. There is a danger that changes in one dimension may be masked by changes in the opposite direction in another dimension. Furthermore, figures used in calculating the multi-dimensional variable may also be present in other variables, exacerbating problems of collinearity. For these reasons when carrying out the principal component and regression analysis only individual variables representing specific, distinct aspects of deprivation were used, rather than using multi-dimensional variables that seek to capture all aspects of deprivation.

For the correlation analysis, however, multi-dimensional variables were used, with two different approaches being employed to represent deprivation and capture its multiple elements. The first of these is a statistic published as part of the UK census that represents the number of households in each LSOA experiencing 0, 1, 2, 3 or 4 dimensions of deprivation. The dimensions used in calculating this variable are employment, education, health and disability, and housing. Notably, income is not considered directly in this statistic.

The second approach to representing the multi-dimensional nature of deprivation in the correlation analysis was the use of the indices of deprivation published by the UK Department of Communities and Local Government (DCLG), the most recent figures available at the time of analysis being from 2010. These indices assume deprivation to encompass a general lack of access to both resources and opportunities and for the 2010 release were built from 38 indicators covering seven broad domains. Separate indices are available for each of the seven domains—income; employment; health and disability; eduction, skills and training; barriers to housing; crime; and living environment. The index most commonly used, however, is the Index of Multiple Deprivation (IMD). The IMD combines values from all seven domains, applying different weights to each, in order to produce a composite indicator of the relative level of deprivation in an area [25].

The indices of deprivation have been widely used in the context of English policy making, but have a number of problems as far as statistical analysis is concerned. In addition to the general challenges of multi-dimensional variables already discussed, with some notable exceptions[2] the indices of deprivation are ordinal, not scalar. That is, if area A has an index twice that of area B it is possible to say that area A is more deprived than area B, but not that A is twice as deprived [26]. An important consequence of their ordinal nature is that the indices are not suitable for use with parametric statistical tests.

2.5 Correlation

To explore the relationship between the fire index and the range of potential predictor variables, two simple correlations, Pearson's r and Spearman's ρ, were calculated. Pearson's r was not calculated for those indices of deprivation that are ordinal rather than scalar (see section 2.4.1).

2.6 Principal component analysis

Principal Component Analysis (PCA) was used to identify the important and unique components contributing to differences between LSOAs. Since the principal components

[2] The domains of income and employment are scalar and each covers a single dimension.

identified in PCA are not related to each other it is also valuable in addressing problems of collinearity in predicator variables [27]. The identified components were then rotated using varimax rotation in an attempt to align real world variables to the components extracted. Varimax was chosen as it tends to ensure that each component has only a small number of variables with large loadings and many variables with small or zero loading [28] and is thus well suited to the present purpose.

The process of extracting useful results from the principal component analysis involved multiple iterations. Initially all the available predictor variables were included in the PCA, other than the multi-dimensional variables representing deprivation (see section 2.4.1). Later iterations used some composite variables formed by combining related ethnic groups that had previously been seen to load on the same component; in particular, Asian Pakistani and Asian Bangladeshi were combined (ie the two variables were summed into a single new variable), as were Black Caribbean, Black African and Black Other. White British was excluded because of its tendency to load negatively on any component against which another ethnic group loaded strongly.

Finally, smaller ethnic groups were excluded in later iterations, leaving Asian Pakistani and Bangladeshi, Asian Indian, Black, mixed Black / White and other White. This decision was taken on pragmatic grounds because including a large numbers of smaller groups tended to lead to poor convergence in the varimax rotation.

The assessment of how many components to extract was based on interpretation of the scree plot [29]. This is a somewhat subjective approach and varimax rotation is known to be sensitive to both over and under extraction [30]. The advice of Costello and Osborne [31] was followed, testing with one or two factors either side of the apparent point of inflection. To protect against factor splitting, in some iterations 12 dummy variables were added and populated using the SPSS function RV.UNIFORM(0,1), following the advice of Wood et al. [30].

2.7 Regression

Ordinary least squares regression analysis was undertaken with the ADF index as the criterion variable. The forced entry method was used as this approach leaves decisions on which variables to include to the investigator, rather than the software. As with the PCA, this process was iterative. The initial choice of predictor variables was based on the outcomes of the PCA. Subsequently, variables that had no significant impact upon the regression were removed; additional variables that had loaded highly in some of the PCA runs were introduced and tested; potential signs of collinearity were monitored, in particular the Variance Inflation Factor (VIF), and adjustments made where collinearity became evident. As a final check, because of the apparent lack of normality in the variables, bootstrapping was used to confirm results, using 5 000 samples and a confidence interval of 95%.

3 Results and discussion

3.1 Correlation

Due to the number of LSOAs considered (n=1680) the threshold for testing the significance of both Pearson's r and Spearman's ρ was extremely low, rendering significance a poor discriminator of the importance of identified correlations. Using a one-tailed test, only four of the predictors considered had correlations that were not significant at the 0.01 level, and of those one was significant at the 0.05 level. Accordingly a cut off for r of 0.4 has been adopted, as the lower end of the range considered to represent moderate correlation by Evans [32], and those predictors with an absolute value exceeding this level in either test are shown in Table 2. From these results it can be seen that three identifiable groups of factors emerged as being strongly positively associated with rates of ADF.

The first group of important factors concerns multiple aspects of deprivation. Worklessness is the aspect which appears most strongly associated with high accidental dwelling fire rates, but income, health and housing also feature. The overcrowding index is a measure of housing deprivation that represents the difference between the number of bedrooms in a dwelling and the number of bedrooms that the occupying household is deemed to need according to a standard formula.

A second group of associations comprised areas with a high proportion of the population identifying as Black African, Black Caribbean or Black Other. As some have argued that this association is the result of collinearity with other factors [16] a partial correlation was undertaken, controlling for income deprivation, employment deprivation, lone parents, households with social landlords and never having worked. Although controlling for these factors did considerably reduce the correlation coefficient it did not eliminate it (Black, all r=0.204).

The final set of associations relates to areas with high concentrations of single person households. Links between fire rates and single person households have been reported before [22,33], but previous research has not noted the influence of the age of individuals living alone. Those under 65, and in particular those in the 35-54 age bracket, appear to be an important group whose presence is strongly linked to higher rates of accidental dwelling fire. In contrast, a high concentration of those living alone and 65 or over shows only a weak association with rates of fire, and that is negative. These results are presented in more detail in Table 3.

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Predictor	Spearman's ρ	*Pearson's r*
Households with social landlords	0.425	0.440
Black African	0.449	0.461
Black Other	0.405	0.409
Black, all	0.440	0.467
Never worked	0.480	0.429
Not worked for over 5 years or never worked	0.420	0.407
Not worked for over 10 years or never worked	0.448	0.425
Households with 0 dimensions of deprivation	-0.439	-0.426
Households with 3 dimensions of deprivation	0.464	0.478
Households with 4 dimensions of deprivation	0.459	0.468
Households with 2 or more dimensions of deprivation	0.423	0.417
Households with 3 or more dimensions of deprivation	0.475	0.478
Single person households aged < 65	0.379	0.408
Single person households aged 35 – 54	0.359	0.408
Index of multiple deprivation	0.482	N/A
Index of income deprivation	0.477	0.475
Index of employment deprivation	0.459	0.465
Index of health deprivation	0.442	N/A
Overcrowding index ≤ -1	0.472	0.396
Overcrowding index ≥ 2	-0.496	-0.476
Overcrowding index 0	0.506	0.510
Overcrowding index -1	0.471	0.417
Unemployed and seeking work in week prior to census	0.476	0.492
Long term sick (economically inactive)	0.410	0.397

Table 2: Notable correlations between predictors and the index of fire incidence ($|r| \geq 0.4$)

Age range	Spearman's ρ	Pearson's r
Under 35	0.376	0.334
35-54	0.359	0.408
55-64	0.174	0.202
65 and over	-0.158	-0.134
All under 65	0.379	0.408
All ages	0.271	0.326

Table 3: Correlation between fire rates and number of single person households of various age groups

It is unclear why such a difference exists between working age (i.e. under 65) and older single person households, but a clear difference was also evident in the principal component analysis, which suggested that these are distinct groups living in different areas (see 3.2). In general, those living alone under 65 are more likely to be men, and more likely to have come to solo living as a result of relationship breakdown, whilst those over 65 are more likely to be women and to have outlived a partner [34]. People living alone and of working-age are known to have lower rates of economic activity than the general population, and to be more likely to smoke or drink [35]. With a considerable proportion of dwelling fires attributable to smoking material [2] or associated with drinking [20,33] this may be one mechanism linking the younger group to increased rates of fire. Indeed, there is good evidence that alcohol is an important factor in fire related deaths of those under 60 in particular [36]. It is clear that with the number of people of working age living alone rising rapidly in Britain in recent years [34,35] this finding has important policy implications and merits further investigation.

The weak and negative association seen between the over 65 group and rates of fire is interesting because it stands in contrast to findings elsewhere that older people are more likely to be fire casualties [20–23]. This suggests that older people are no more likely to experience a fire, but if they do then the consequences are likely to be more severe. Difficulty effecting an escape, greater physical vulnerability to injury and poorer recovery may be important factors in this.

3.2 Principal component analysis

Whilst the results of principal component analysis were somewhat sensitive to both the variables included and to the number of factors extracted some clear trends were evident. Scree plots generally suggested that five components be extracted, and the use of dummy random variables confirmed this. Two identifiable components consistently emerged as amongst those with the highest eigenvalues. The first of these loaded strongly on Asian Pakistani and Asian Bangladeshi population, overcrowding, and people who have never worked, with these variables not loading strongly against any other component. This component also tended to load strongly against high numbers of people with poor English and high numbers of people who have not worked for some years (but not necessarily never having worked) and income deprivation, although these latter variables were less discriminatory, also loading against other components. It is worth noting in particular that the numbers of people of Asian Indian origin did not load highly on this component, but often loaded strongly on a separate component. The marked link seen between numbers of Pakistani and Bangladeshi residents and people who have not worked for some time may be at least partly connected to the very low levels of economic activity amongst Pakistani and Bangladeshi women in the UK, a factor that is not seen so strongly amongst Indian women [37]. It is notable that a measure of unemployment, which only considers those who are seeking work, loaded only moderately against this component and also exhibited moderate loadings against several other components. This lends weight to the idea that it is the number of people making a cultural decision to stay at home, rather than those seeking but unable to find work, which is a unique feature of this component.

The second component to emerge consistently across iterations of PCA loaded highly on measures relating to poor health and limiting disability, and on measures relating to poor educational achievement. Why the two apparently quite different issues of health/disability and educational attainment seem to combine remains unclear but moderate (although not discriminant) loading against this component of single person households aged over 65 may offer a clue. Older people are both more likely to suffer ill health and disability, and, given the marked changes in educational patterns in the UK since the mid twentieth century [38], to have lower educational achievement.

A number of other components were found during the process. As already mentioned, a component loading on the Asian Indian population was found to be distinct from the Asian Pakistani and Asian Bangladeshi population. A component loading on Black population (African, Caribbean and Other) was evident in several iterations, as was one loading on single person households aged under 65. This latter variable consistently loaded on a different component to single person households aged 65 and over, reinforcing the idea that these are groups with very different characteristics. Other variables that loaded highly and discriminately on principal components in several iterations were the number of lone parents and the number of people whose ethnicity was mixed White / Black. Notably, there was little evidence of a single component that encompassed all the factors often thought of as related to deprivation. Furthermore, the measure of income deprivation consistently loaded moderately on at least two components, making it a poor choice for discriminating between them.

3.3 Regression

Regression began with those variables identified as loading discriminately on principal components, with variables then added and removed following the process described in section 2.7. The final model used as predictor variables the proportion of people of Black descent, the proportion of single person households aged under 65, and the proportion of people who had not worked for more than 5 years or had never worked. Together, these three variables explained nearly one third of the total variance in the rate of ADF ($R^2 = 0.323$, adjusted $R^2=0.322$), with coefficients shown in Table 4.

The standardised coefficients are all positive and are all of a similar magnitude, suggesting that the three predictor variables exert roughly similar levels of influence over the criterion variable. The Variance Inflation Factors (VIF) for all predictors are relatively low, indicating low levels of collinearity. This is supported by additional collinearity diagnostics, which can be seen in Table 5. The highest variance proportion of a secondary variable on any particular component is 0.29, low in comparison to the primary variables on each dimension (shown in bold).

	Unstandardised coefficients		Standardised coefficients	
	B	SE B	β	VIF
(Constant)	-31.619	6.716		
Black population	249.165	30.440	0.211	1.638
Single person household < 65 years old	264.061	20.785	0.285	1.243
Not worked > 5 years or never	256.233	22.541	0.266	1.357

Notes: $R^2 = 0.323$; all coefficients p<0.001

Table 4: Regression coefficients

Dimension	Eigenvalue	Condition index	Variance proportions			
			(Constant)	Black popn.	Single person HH < 65yr	Not worked > 5 years
1	3.451	1.000	0.00	0.02	0.00	0.01
2	0.392	2.966	0.02	**0.67**	0.01	0.01
3	0.128	5.194	0.02	0.02	0.012	**0.78**
4	0.029	10.922	0.95	0.29	**0.87**	0.20

Table 5: Collinearity diagnostics

Although the standardised residuals fail formal tests of normality ($D(1680)=0.63$, p<0.001) this is unsurprising given the large sample size ($n=1680$) [39], and visual inspection of the distribution reveals a reasonable approximation to normality (Figure 1). Taken together these factors suggest that the model can be considered to be valid.

Previous models that have been reported to explain a greater proportion of the variance [e.g. ,16] have used much larger geographic units than in this study. The aggregation of data will tend to suppress the impact of outliers, resulting in greater explanatory power. Given the large number of potential influences on rates of fire, that three factors can explain nearly one third of the total variance at LSOA level is noteworthy. The strong role of human activity and behaviour in domestic fire initiation [40] suggests that a high proportion of random, unpredictable variance is to be expected. In this context, the explanatory power of this model must be viewed as noteworthy.

It is important to stress that the three predictors used in this model are not the only predictors that could be used to build a reasonable model. Each in effect represents a single complex component and other predictors that load highly on the same component are likely to give similar results. The model presented is thus only one of several possible models, but it is nevertheless of value in understanding the uneven distribution of fire incidents within the West Midlands county and predicting the distribution of future incidents. Through applying the insights from this model resources can be targeted more effectively, from the identification of critical audiences for fire safety information through to the siting of emergency response vehicles.

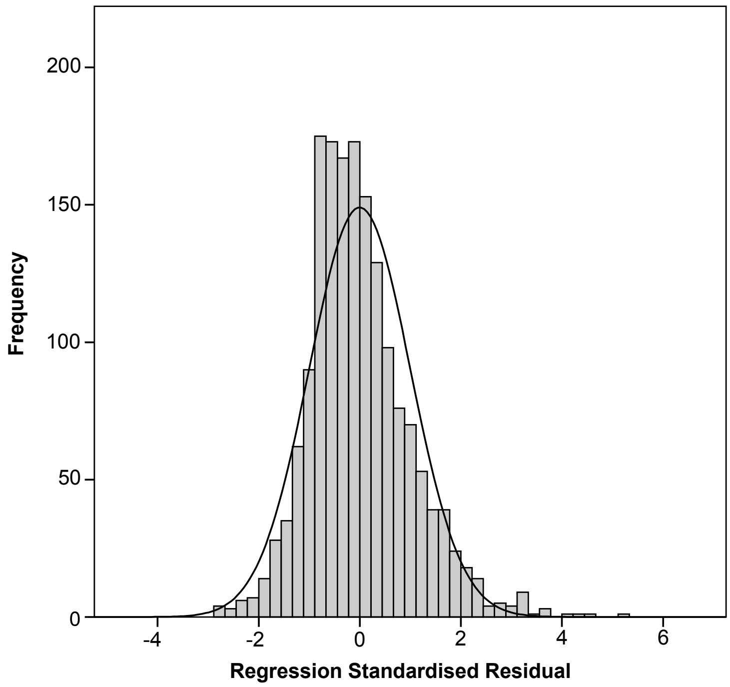

Figure 1: Histogram of standardised residuals with normal distribution curve superimposed

3.4 Limitations

A principal limitation of the current study is that it is ecological in nature. It is vulnerable to ecological fallacy because it does not directly link the variables studied together [41]. The existence of an association at an area level should not be seen as implying that such an association exists at an individual level [42]. For example, whilst these results suggest that those living in areas where there are high numbers of single person households aged under 65 experience higher levels of fire, it is not possible to say that individuals under 65 who live alone experience more fires.

A further limitation comes from the fact that this study effectively involves a whole population. As the cases included do not represent a sample taken from some wider population it is not strictly possible to generalise to a wider population from these results—the results are specific to the West Midlands county. Whilst similar predictors may be found in similar populations, any attempt to transfer these findings to other areas should be qualified by a careful consideration of cultural context and demographic make-up.

The study considered only dwelling fires attended by the WMFS. However, there is evidence that a relatively small percentage of fires occurring in the home are reported to the fire services [43,44]. It is important to be clear, therefore, that what is investigated here is a subset of all domestic fires. Nevertheless, it is reasonable to assume that those fires that do result in calls to the fire service are the more serious ones and the ones most likely to result in substantial loss or injury. They are also the incidents that are of the greatest importance to the service in terms of resource planning and those upon which the service needs to focus to manage demand.

4 Conclusions

Despite a substantial reduction in rates of fire in the UK in recent years it is clear that in the large urban area that forms the basis of this study there continues to be considerable inequality in the way in which accidental dwelling fires are distributed through society. Whilst many socio-demographic factors correlate with rates of ADF, their high levels of collinearity make it difficult to discern, on the basis of correlations alone, which factors are most useful in understanding the distribution of fire and in targeting future interventions. Principal component analysis provides a useful tool to help understand the links between the many potential predictors available and to minimise collinearity by identifying a small number of variables that act in relative independence. By combining PCA with linear regression it is possible to produce a model that uses a small number of predictor variables whilst explaining around a third of the variance in rates of fire at a small neighbourhood level.

In line with earlier work, this study confirms that the ethnic make-up of an area, particularly the proportion of Black African and Caribbean residents, and the economic deprivation present in an area, most notably levels of worklessness, are strongly indicative of rates of fire. In addition it reveals a clear, and unreported, link to the proportion of single people in middle age groups living in an area. This is an insight that is of considerable value to fire services, made all the more important by the fact that this latter group is growing in numbers in the UK.

Community fire safety and prevention work has become an increasingly significant part of the role of fire services in the UK since the mid-1990s [45] and is now a statutory duty. The findings of this study will help fire services to improve the targeting of fire safety interventions and to focus on those neighbourhoods and communities where interventions are most needed and have the greatest potential to reduce both response demand and inequality. They also have value in helping plan the location of emergency response resources.

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